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Robust Principal Component Analysis for micro-Doppler based automatic target recognition

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Abstract

Dealing with real data it is likely that it will exhibit the presence of unexpected observations within the data which can affect the correct reduction of the representative features of a target signature. For the specific case of micro-Doppler based classification this problem can appear in the feature selection stage. To address this problem the Robust PCA based on the Minimum Covariance Determinant (MCD) estimator is introduced. The proposed technique showed to improve the overall classification accuracy.

1. Introduction

The presence of internal motions on moving radar targets introduce signal modulations known as micro-Doppler (m-D) [Chen (2010)]. This phenomenon can be exploited to characterize the target time-frequency radar response in order to classify and identify the target [Molchanov (2012), Bjorklund (2012), Kim (2009)]. Specifically, the classification of moving ground targets, including humans and animals, has potential applications relating to tasks such as surveillance and border control [Molchanov (2012), Bilik (2006)]. Compared with visual image sequences, radar micro-Doppler signatures are not sensitive to distance, light conditions and background complexity, which is advantageous for the purposes of estimating gait characteristics.

The main contribution of this paper is the presentation of a new application of the Robust Principal Component Analysis (RPCA) [Russeeuw (1985), Rousseeuw (1999), Beltramonte (2009)], to improve the performances of the classification algorithm. When using real data it is likely that it will exhibit the presence of unexpected observations (outliers) within the data which can affect the correct reduction of the representative features of the signature. This causes an incorrect projection of the data along the principal components, which then results in an incorrect de-correlation of the different features. To address this problem the PCA is replaced by a Robust PCA based on the MCD estimator. The proposed approach is tested using three algorithms that were developed to perform feature extraction from m-D signals [Miller (2013)]. Features produced by each of these algorithms were used for classification of real X-band radar data containing micro-Doppler of six classes of human and animal motions. The remainder of the paper is organised as follows. Section II introduces the RPCA, while Section III provides an overview of the the feature extraction algorithms used to test the approach. Section IV shows the effectiveness of the proposed techniques with results on real X-Band data, while Section V concludes the paper.

2. Robust PCA

As a feature vector may contain a high number of components, it would increase the computational burden of the classification stage. For this reason the number of components needs to be reduced, while retaining a good discrimination property of the feature. A solution is found in the Principal Component Analysis (PCA) [Joliffe], to extract a reduced set of components of the feature vector. In addition, the PCA de-correlates the components of the feature vector, and so it increases the significance of each component and reduces redundancy. This means that the same amount of information can be obtained with a smaller feature dimension.
However dealing with real data can imply the presence of unexpected observations within the data to be processed with the PCA. This means that the estimation of the transformation matrix is influenced by these outliers. This causes an incorrect projection of the data along the principal components, which then results in an incorrect de-correlation of the different features.
To solve this problem we replace the PCA with a Robust PCA (RPCA) based on the Minimum Covariance Determinant (MCD) estimator [Russeeuw (1985)]. The first operation to reduce this effect is to identify the anomalies and discard them for the estimation of covariance matrix used by PCA to re-project the data. One way to identify possible multivariate outliers is to calculate a distance from each point to the "center" of the data. An outlier would be a point with distance larger than some predetermined value. Given n data points $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_n\}$ in p dimensions, a conventional measurement of quadratic distance from a point $\mathbf{x}_i$ to a location $T(\mathbf{X})$ given a shape $\mathbf{S}$ in the multivariate setting is:

$$d_i^2 = (\mathbf{x}_i - T(\mathbf{X}))^T \mathbf{S}^{-1} (\mathbf{x}_i - T(\mathbf{X})) \tag{2.1}$$

This quadratic form is called the *Mahalonbis squared distance* (MSD). An outlier can be thought as a point with large MSD from the center. However, the Mahalanobis distances suffer from masking because the conventional location and shape parameters are not robust to outliers. Indeed atypical multivariate vectors of observations will tend to deflate correlations and possibly inflate variances. This will decrease the Mahalanobis distance for the atypical observation and distort the rest of the plot. The use of distances based on robust estimators of multivariate location and scatter is aimed to mitigate this effect. A robust location and shape estimate is possible with the *Minimum Covariance Determinant* (MCD) estimator [Russeeuw (1985)]. In general, the MCD of $\mathbf{X}$ is the mean and covariance matrix based on the sample of size h ($h \leq n$) that minimizes the determinant of the covariance matrix.

$$MCD = \left(\bar{\mathbf{X}}_J^*, \mathbf{S}_J^*\right) \qquad \text{where} \qquad J = \{\text{set of } h \text{ points: } |\mathbf{S}_J^*| \leq |\mathbf{S}_K^*| \, \forall \text{ set K: } \# |K| = h\} \tag{2.2}$$

$\# |\omega|$ is the number of elements in the set ω and:

$$T(\mathbf{X}) = \bar{\mathbf{X}}_J^* = \frac{1}{h} \sum_{i \in J} \mathbf{x}_i \qquad \mathbf{S}_J^* = \frac{1}{h} \sum_{i \in J} \left(\mathbf{x}_i - \bar{\mathbf{X}}_J^*\right) \left(\mathbf{x}_i - \bar{\mathbf{X}}_J^*\right)^T \tag{2.3}$$

A robust covariance matrix estimator is now available and the value h can be thought of as the minimum number of points that must not be outlying. The sample mean of these h values is the estimator of the multivariate location, while the sample covariance matrix is the estimator of the multivariate scatter. To quantify correctly the h value, the notion of the *breakdown point* of an estimator T is introduced. $\mathbf{X}'$ is obtained by replacing any m of the original data points by arbitrary values, the maximal bias between the corrupted and the original data set is defined as:

$$\beta(m; T, \mathbf{X}) = \sup_{\mathbf{X}'} \left\| T\left(\mathbf{X}'\right) - T\left(\mathbf{X}\right) \right\| \tag{2.4}$$

so the *breakdown point*

$$\epsilon_n^* \left(T, \mathbf{X}\right) = \min \left\{ m/n; \beta\left(m; T, \mathbf{X}\right) \text{ is infinite} \right\} \tag{2.5}$$

is the smallest fraction of contamination that can cause T to take on values arbitrarily high. An estimator with a breakdown point equal to 50% is the most desirable: this value is certainly the best that can be expected because for larger amounts of contamination, it becomes impossible to distinguish between the "good" and the "bad" parts of the sample. The Minimum Covariance Determinant estimator is capable to safeguard against up to 50% of outliers because it tries to use only the good part of the samples [Russeeuw (1985)].

3. Feature Extraction Algorithms

Many approaches to micro-Doppler feature extraction have been documented where the aim has been to generate feature sets which are useful for a subsequent classification stage to identify the type of motion present in the original micro-Doppler observation. In many cases the first stage of feature extraction is to perform time-frequency analysis (TFA) of the Doppler signal [Molchanov (2012), Bjorklund (2012), Kim (2009)], in order to highlight time varying information. Each of the algorithms which will be described in this section rely on time-frequency analysis, and specifically the short time Fourier transform (STFT), as a first step in extracting features from micro-Doppler signatures.

The SPF algorithm: The spectrogram frequency profile (SFP) algorithm generates a feature vector from the spectrogram of a micro-Doppler signal (gained via the STFT) simply by summing over time for each of the frequency bins. The resultant feature vector is the average over time of the spectrum of the Doppler signal.

The CVDFP algorithm: One shortcoming of the SFP algorithm is that it does not exploit the time varying information about the instantaneous frequency contained in the time-frequency distribution. The cadence velocity diagram frequency profile (CVDFP) algorithm was therefore developed in an attempt to create an algorithm that would generate features which benefit from the localisation in time property of the STFT. A signals cadence velocity diagram (CVD) is formed from its spectrogram, as described in [Bjorklund (2012)], taking the Fourier transform along the time dimension for each frequency bin. The result is a matrix whose rows represent Doppler frequency (or target velocity since the two are directly proportional) and whose columns represent cadence frequency, which is a measure of how often different frequencies occur over time within the signal. Just as the SFP algorithm creates a feature vector by summing over time for each Doppler frequency bin of the spectrogram, the CVDFP algorithm creates a feature vector by summing over cadence frequency for each Doppler frequency (or velocity) bin of the CVD.

The SFP-CVDFP-PCA algorithm: Preliminary investigations [Miller (2013)] demonstrated that both the SFP and CVDFP algorithms were capable of generating features which led to good classification performance when using a support vector machine (SVM) classifier to classify micro-Doppler of humans and animals. These preliminary tests also indicated that the feature vectors generated by the two algorithms were significantly correlated. The SFP-CVDFP-PCA algorithm uses principal component analysis to remove redundancy between the correlated SFP and CVDFP feature vectors, and to generate a new feature vector which contains information from each of these which is useful for classification. The first step of the SFP-CVDFP-PCA algorithm is to take the logarithm of the SFP and CVDFP feature values. The second step of the algorithm is to perform PCA on the SFP and CVDFP features. The final step of the SFP-CVDFP-PCA algorithm is to form the feature vector by discarding principal component 2.

Feature dimensionality reduction: Regardless of the algorithm used to generate feature vectors from each observation of micro-Doppler data, the following stage in the feature extraction process is the application of PCA for dimensionality reduction of features. The majority of variation in the data is explained by few low ordered components while the higher order components account for little variation in the data and can in fact identify nearconstant linear relationships between the original features [Joliffe]. The data-reduced feature set can therefore be seen as a more efficient representation of the original data in which the underlying structure is retained despite the loss of some information. Three methods of dimensionality reduction were evaluated. The first method uses standard PCA to reduce the number of features, without making any attempt to reduce the effects of outliers. The second method replaces PCA with RPCA. In the third method, standard PCA is performed to reduce the dimensionality of the data, and then RPCA is performed on the resulting data to remove the effects of outliers without performing any further dimensionality reduction.

4. Experimental results

The feature extraction methods described here were applied to X-band radar data of moving humans and animals. The dataset used was generated during a single test using a Selex ES PicoSAR system operating in GMTI mode (using a carrier frequency of 9.2 GHz and PRF of 2kHz). The radar was used to target a fixed scene from a ground-based platform. Humans and/or horses were then introduced to the scene to act as targets. Data was collected for targets performing each of the following classes of motion: Human Walking (slow); Human Walking (medium); Human Walking (fast); Horse With Rider Walking (medium); Horse With Rider Walking (fast); Horse and Human Both Present. The dataset consists of 28 observations for each class of motion where the duration of each observation is 0.5s. The exception to this is class 6 for which there are 112 observations. Classification of extracted feature vectors was performed using an SVM classifier with a radial basis function (RBF) kernel, employing a cross-validation grid search for selection of cost function and kernel parameters. The one-against-all approach was used to perform multi-class classification between the six classes. When classifying the test dataset, a system of Monte Carlo testing was applied whereby classification was performed repeatedly using randomly generated permutations of training and test for each repetition. For each test 50 repetitions were carried out, and a ratio of roughly 70% training data to 30% test data was maintained throughout testing. Each of the feature extraction algorithms described in section 3 were tested and compared using standard PCA, Robust PCA, and PCA followed by RPCA for feature reduction. In Figure 1, Figure 2 and Figure 3 the classification accuracy obtained from the three algorithms are shown. From Figure 1 and Figure 2 marginal improvements or no-improvements are observable in the use of the RPCA alone or after the PCA stage. In Figure 3 the best results are achieved in terms of classification, in addition these are maximized by the use of the RPCA after the PCA stage leading to a maximum classification accuracy of 93.52%. This result can be explained by the fact that after the PCA stage and the dimensionality

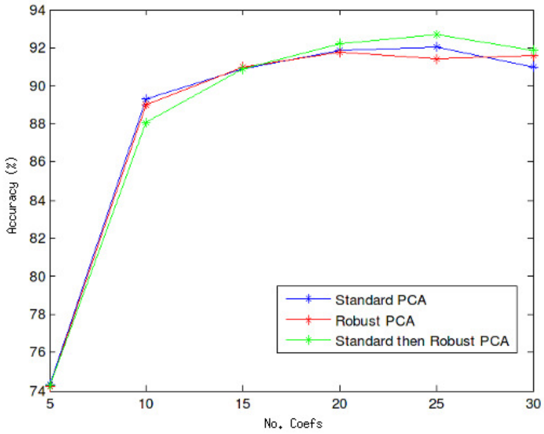

FIGURE 1. Classification results obtained using the SFP algorithm and different dimensionality reduction approaches.

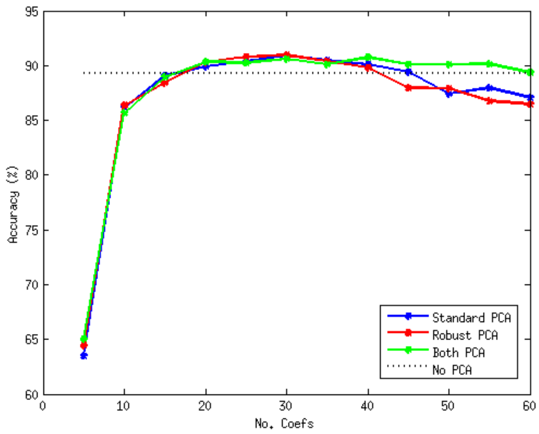

FIGURE 2. Classification results obtained using the CVDFP algorithm and different dimensionality reduction approaches.

reduction the RPCA can produce a better estimate of the principal components, leading to more characterizing features.

5. Conclusion

In this paper the application of the Robust PCA for micro-Doppler feature classification purposes was presented. High classification accuracies were achieved particularly when the SFP-CVDFP-PCA was used. The use of the RPCA was shown to be effective in deriving more characterizing micro-Doppler features. Further development of this work will be the extension of the algorithm to be scene independent through a clutter removal algorithm.

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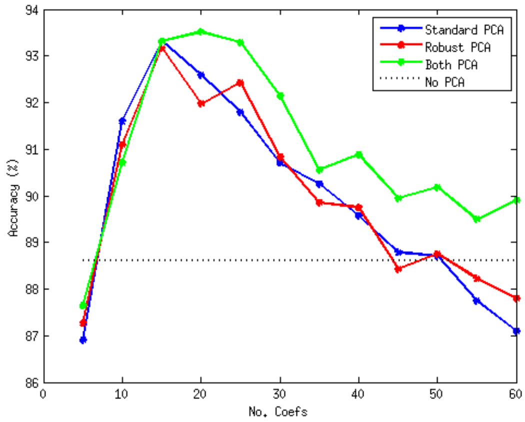

FIGURE 3. Classification results obtained using the SFP-CVDFP-PCA algorithm and different dimensionality reduction approaches.

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